IMPLEMENTATION OF PARETO-ARCHIVE NSGA-II ALGORITHMS TO A NEARLY-ZERO-ENERGY BUILDING OPTIMISATION PROBLEM

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ABSTRACT

Finding cost-optimal solutions for nearly-zero energy buildings (nZEB) according to the new recast of the European Energy Performance of Buildings Directive EPBD- recast 2010 is a challenging task that requires exploring numerous possible combinations of energy-saving and energy-supply measures. Multi-objective simulation-based optimisation can be effectively used to find solutions close-to the Pareto-optimal front. The current study tests the performance of three optimisation algorithms based on NSGA-II (elitist non-dominated sorting genetic algorithm, by Deb et al. 2002) in finding the cost-optimal and nZEB solutions for a problem that has a large discrete solution-space. Optimisation runs with low number of evaluations show that a presented active-archive strategy (unconstrained archive for possible non-dominated adult solutions) can significantly improve the repeatability of the original NSGA-II in finding a diverse set of solutions near-to the true Pareto-optimal front.

INTRODUCTION

Efficient multi-objective optimisation algorithms are needed to find the cost-optimal and nZEB integrated solutions without a need for numerous time-consuming simulations. Because of the discontinuity of the objective functions in such problems, optimisation algorithms that require smoothness were found not efficient (Wetter and Wright, 2004; Pernodet et al., 2009). Multi-objective evolutionary algorithms (MOEAs) that do not require smoothness were used for the design of Green Buildings (Wang et al, 2005) and to improve the energy consumption of net-zero energy solar homes (Charron et al, 2006). Elitist MOEAs (e.g., NSGA-II) offer great potential for implementations in this field. However and because of their stochastic operators, they could occasionally fail to get close to the Pareto-optimal front, particularly if a low number of iterations is implemented as a stopping criterion (Palonen et al, 2009; Hamdy et al., 2009). In order to avoid this, archives can be added to NSGA-II.

This is paper is one of the first studies that use simulation-based optimisation in finding the cost-optimal and nZEB solutions for a problem that is in accordance with the implementation of the new EPBD-2010. In this study, the performance of three algorithms based on NSGA-II, with passive and active archiving strategies are tested. The problem has a discrete solution space of energy saving measures and energy supply systems options, including renewable energy sources (RES). To the knowledge of the authors, implementations of NSGA-II with an active archive strategy (unconstrained archive for possible non-dominated adult solutions) on HVAC and building optimisation problems are not existing in the literature The repeatability of the results of the three algorithms is investigated using different numbers of simulation evaluations. The investigated algorithms and their performance criteria are described in the next section, which is followed by a description of the nZEB optimisation problem. After that, the performances of the algorithms are shown on the nZEB problem and on benchmark tests.

THE OPTIMISATION ALGORITHMS

In this study, three algorithms are tested using an in-house modified version of GenOpt (GenOpt, 2011).

GenOpt is an optimisation program for the minimization of a single objective function that is evaluated by an external simulation program. Besides being a single objective program, there are no evolutionary algorithms in the GenOpt library. The current contribution implements three multi-objective genetic algorithms

- the original NSGA-II

and two others based on it

- pNSGA-II, and
- aNSGA-II.

in GenOpt.

NSGA-II (Deb et al., 2002) is a well-known elitist algorithm used widely in different fields. NSGA-II implements elitism by maintaining two populations of size *N*. The adult population *P* from the previous generation and the child population *Q* generated at the current generation. At each generation, these populations are combined and sorted according to the non-domination concept. Then *N* solutions are selected as the next parent population *P*. The number of non-dominated points available after sorting may be greater than the populations size *N*, which defines the number of (elite) points that are kept by the algorithm. When the number of the available non-dominated points is greater than *N*, NSGA-II selects the *N* least crowded solutions by using the crowding distance measure and rejects the rest of the non-dominated points.

pNSGA-II is NSGA-II with a passive archive. The solutions that would be rejected by the original NSGA-II are saved in an archive. The passive archive works simply as storage for the evaluated solutions. Its members do not act in the solution generation procedure. As a last step of the algorithm, the non-dominated solutions are identified from the archive and are added to the final population. NSGA-II with such kind of archive strategy was used in a number of buildings and HVAC design optimisation problems (e.g. Hamdy et al., 2011a; Hamdy et al., 2011b).

aNSGA-II is NSGA-II with an active archive. The archive keeps also all the non-dominated points that would be rejected by the original NSGA-II. However, its members participate in the solution generation procedure. The saved non-dominated points supplement the diversity and allow using a small parent population size. When the size of the parent population is small, high quality (non-dominated) solutions are used more frequently than dominated solutions. This is expected to increase the rate of the convergence.

The performance of these three algorithms is assessed in terms of the following criteria:

- Convergence to the Pareto-optimal set (Generational Distance), denoted by *GD*,
- Diversity of solutions in the Pareto-optimal set, denoted by *DIV*, and
- Number of solutions on the Pareto-optimal set, denoted by *NS*.

The Generational Distance *GD* (Deb, 2001) is used as a convergence metric in this study. This metric finds an average Euclidean distance between the true Pareto-front *P** and the solution set *S* obtained by each algorithm and as follows:

$$GD = \sum_{i=1}^{|S|} d_i \frac{1}{|S|} \qquad (1)$$

where d_i is the Euclidean distance (in the objective space) between the solution $i \in S$ and the nearest member of *P**.

The Diversity of solution set returned by the algorithm *DIV* is measured using diversity metric from (Deb et al, 2002):

$$DIV = \frac{d_f + d_l + \sum_{i=1}^{N-1} |d_i - \bar{d}|}{d_f + d_l + (N-1)\bar{d}} \qquad (2)$$

where d_i is the Euclidean distance between the consecutive solutions in the obtained non-dominated set of solutions and $\bar{d}$ is the average of all distances d_i (i=1,..,N), assuming there are N solutions in the obtained non-dominated set. The parameters d_f and d_l are the Euclidean distances between the extreme and the boundary solutions (Deb et al., 2002). This metric gives smaller values to better distributions. The number of the obtained non-dominated solutions (*P** members) is denoted by *NS*.

THE OPTIMISATION PROBLEM

The investigated algorithms are tested in an optimisation problem to find the optimal trade-off relations between the primary energy consumption (PEC) and the life cycle cost (LCC) for a single-family house located in Finland. These two objective functions (PEC and LCC) are the targets that the European Energy Performance of Buildings Directive recast (EPBD, 2010) defined to be assessed to find the environmental and economic impacts of buildings (BPIE, 2010). The EPBD indicates that all new buildings should be nearly-zero energy buildings (nZEB) by the end of 2020, and two years prior to that for public buildings. According to the EPBD, the cost-optimal solutions should be found among ranges of combinations of compatible energy efficiency and energy supply measures. These combinations should range from those in compliance with the current regulations to combinations that realize nZEBs. Those should also include various options for renewable energy generation. Figure 1 shows the cost-optimal curve that would be found from the assessment. The lowest part of the curve (the economic optimum) is the cost-optimal solution. The part of the curve to the right of the economic optimum represents solutions that underperform in both aspects (environmental and economic). The left part of the curve, starting from the economic optimum point, represents the optimal solutions towards nearly-zero energy buildings, where the extreme left of the curve is the nZEB optimal solution. The aim of this study is to find the optimal curve (between the cost-optimal economic point and the nZEB solution) by taking this problem as a minimization problem of the two objective functions (PEC and LCC).

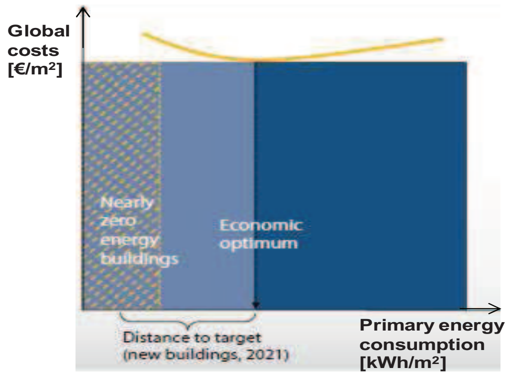

Figure 1 cost-optimality and nZEB (BPIE, 2010)

The studied house has two floors with a total floor area of (156 m^2), Figure 2. There are three options for the house envelope (according to the Finnish C3-2010, low energy, or passive house regulations). All of the windows are shaded to avoid summer overheating: recess shading is implemented in all windows. In addition, overhangs are used for the south zones on the upper floor. No mechanical cooling is used.

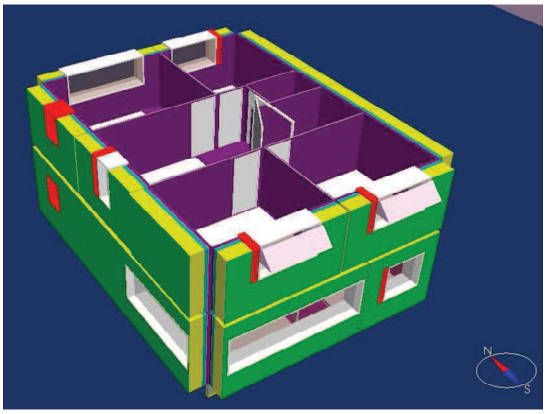

Figure 2 The studied single-family house

Four options for a primary heating unit (HU-1) are offered: indirect electric heating (EH), district heating (DH), Ground Source Heat Pump (GSHP), or Polymer Electrolyte Membrane (PEM) fuel cell. The size of any of these units can cover 50, 60, 70, 80, 90 or 100% of the total peak heating load for both space heating (under-floor heating and ventilation air) and domestic hot water of the house. HU-1 can supply hot water at a temperature from 40 to 60 ^{o}C to the storage tank. However, in case HU-1 is not able to meet the required peak heat load or operating temperature, an auxiliary heating unit (HU-2) can be put into operation with two options: electric-heater or gas boiler. The air ventilation system is a supply and exhaust system with (60, 70 or 80% efficiency) exhaust air heat recovery unit. The on-site electricity generation can be done by a roof-mounted micro-wind turbine (µWT), photovoltaic panel (PV), or the previously mentioned PEM fuel cell. There are different sizes of the micro-wind and areas of the PV panels. The renewable energy source options are given to find the nZEB solution. Net-ZEB solutions, which can balance their net energy on an annual basis, are not expected because it is assumed that there is no energy export to the grid, which is the current situation in Finland. The design-variable options are summarized in Table 1.

The building energy performance and the photovoltaic electricity production are simulated by using IDA-ICE 4.0 (IDA-ICE 2011) and IDA-ESBO 1.0 (IDA-ESBO 2011), respectively. The micro-wind operation is modeled as a function of the prevailing mean wind speed (Figure 3). Partial load operation is considered in the performance of the PEM fuel cell (Figure 4) and GSHP (Figure 5).

Table 1 Design variables

DESIGN VARIABLES	OPTIONS
Building envelope	C3-2010, low energy, or passive house
Type of primary heating unit (HU-1)	Indirect electrical heating, District heating, GSHP, or PEM fuel cell
Type of auxiliary heating unit (HU-2)	Electric heater or gas boiler
Size of µWT [W]	0, 120, 400, or 950
Heat recovery efficiency η	60, 70, or 80 %
Photovoltaic area [m^2]	From 0 to 60 m^2(3 m^{2}step)
T_{out} from HU-1 [^{o}C]	40, 44, 48, 52, 58 or 60 ^{o}C
Size of the heating coil of the DHW tank (% of the max. size)	50, 60, 70, 80, 90, or 100 %
Size of HU-1 (% of the peak heating load)	50, 60, 70, 80, 90, or 100 %

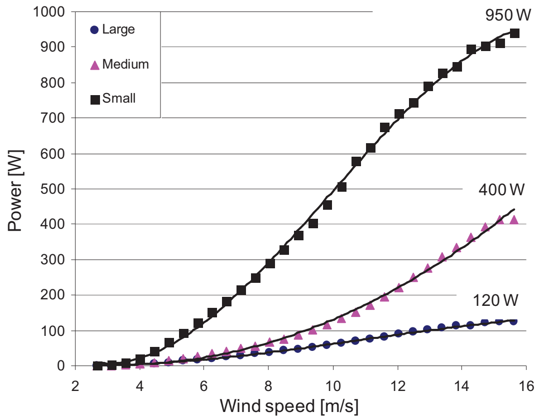

*Figure 3 Performance curves of the micro-wind turbines as a function of wind speed (*Wind-Works, 2003*)*

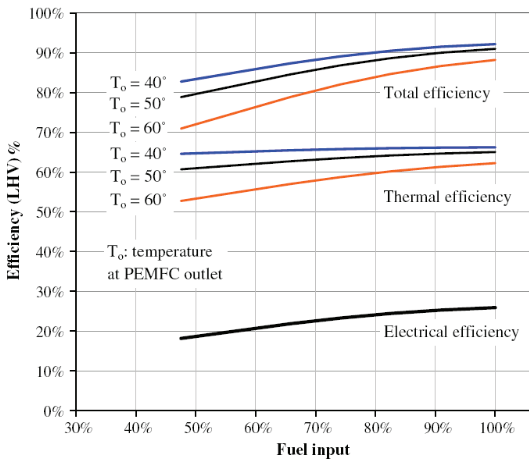

Figure 4 Performance curves of the PEM fuel cell at different outlet water temperatures (*Dorer. 2009*)

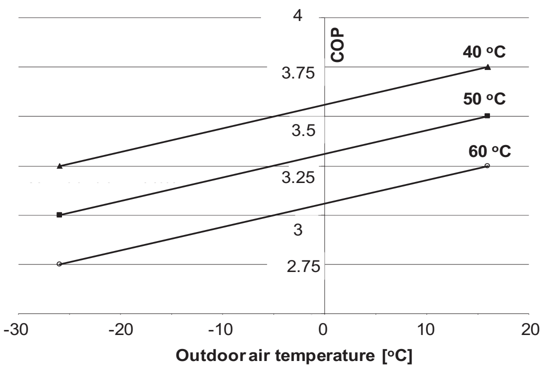

Figure 5 COP of the GSHP at different outdoor and supply water temperatures

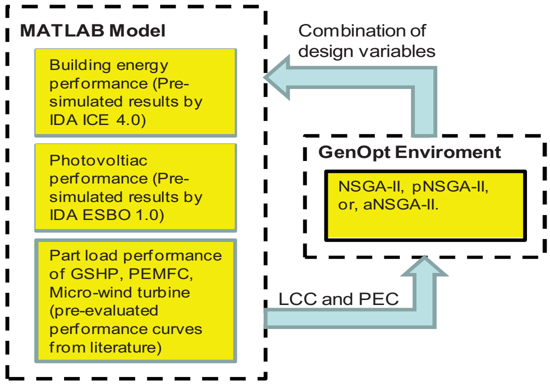

Figure 6 MATLAB-GenOpt scheme

Since we are calculating the primary energy consumption (PEC), different primary energy factors (kWh_p/kWh) for different types of energy source (Hastings. 2010) are considered: 2.35 for electricity, 0.77 for district heating and 1.14 for natural gas to the PEM fuel cell. The life-cycle cost (LCC) is calculated as the sum of the initial cost, replacement cost, operating energy cost and maintenance cost for 30 years discounted to net present values using different energy prices and escalation rates depending on the type of the source energy. Since the current investigation aims to compare different designs, the absolute value of the LCC is not calculated, but the difference ($dLCC_i$) between the LCC for any design (LCC_i) and that for the reference design (LCC_r).

$$dLCC_i = LCC_i - LCC_r \tag{3}$$

The reference design house is in accordance with the current building code (C3-2010). It is connected to the electricity grid and the district heating network, which can cover the full peak loads and supplies hot water at 60°C. It has an exhaust-air heat recovery with an annual efficiency of 60%.

In order to evaluate the energy and economic performance of the combinations of the design variables, a simple simulation model is developed using MATLAB R2008b. The link between MATLAB and GenOpt is shown in Figure 6. The model is based on post-processing of full year hourly simulation results of the three designs of the building envelope and pre-evaluated performance of the energy source systems (µWT, PEMFC and GSHP). The simplified model provides very fast evaluations. The execution time of one evaluation is < 2 seconds. This allows doing a very comprehensive search of the true-Pareto front, which will be used for the verification of the results of the three tested algorithms. The true-Pareto front is found in one month by an exhaustive search exploring 1,306,368 (3×4×2×4×3×21×6×6×6) combinations of the design-variable options.

PERFORMANCE RESULTS

The performance of the three-optimisation algorithms (NSGA-II, pNSGA-II, and aNSGA-II) is evaluated under a comparative framework. In order to specify their features, each one of them is used in 100 times repeated optimisation runs. Initially, a fixed population size (six individuals) and 30 generations are used to provide 180 evaluations for each optimisation run. The idea in using such a low number of evaluations is to minimize the total required time because building simulation is often very time-consuming. Therefore, large number of simulations could not be practical. Instead of the mentioned one-month exhaustive search, the optimisation (180 evaluations) spends about six minutes.

Figure 7 shows the convergence metric (the generational distance *GD*) for the 100-optimisation runs. Lower values of *GD* indicate better convergences to the true-Pareto front. Figure 8 shows the optimisation solutions for the best and worst convergence cases of the 100-optimisation runs. Table 2 presents the divergence *DIV* and the number of solutions *NS* on the Pareto-front in the best and worst convergence runs. These results show that pNSGA-II and aNSGA-II produce larger number of solutions on the Pareto-front *NS* than the original NSGA-II. Hence, it is not fair to compare *GD* and *DIV* of NSGA-II with those of the other two algorithms. However, pNSGA-II and aNSGA-II can be compared with each other because they have close number of solutions. From Figures 7 and 8, we can conclude that aNSGA-II has better convergence. This is because aNSGA-II continues to converge during the optimisation process while NSGA-II and pNSGA-II create oscillating estimates of the true Pareto front. The diversity of the two algorithms with the archive strategies is quite close (Table 2).

The diversity metric *DIV* is affected by *NS*, the number of solutions obtained on the non-dominated front, because *DIV* gives lower values for lower numbers of *NS*. This can be seen from the Table 2, where the original NSGA-II algorithm got the lowest value with six points and aNSGA-II got the higher value with 22 points. Besides, the shape of the true Pareto-front in the optimisation problem is disconnected and the distribution of the disconnected regions is not uniform, which affects the diversity metric as well.

Table 2 DIV and NS achieved in the best and worst convergence runs using 180 evaluations in each run

ALGORITHM	*BEST RUN*		*WORST RUN*	
	DIV	*NS*	*DIV*	*NS*
NSGA-II	0.55	6	0.81	6
pNSGA-II	1.27	22	1.31	18
aNSGA-II	1.35	24	1.07	22

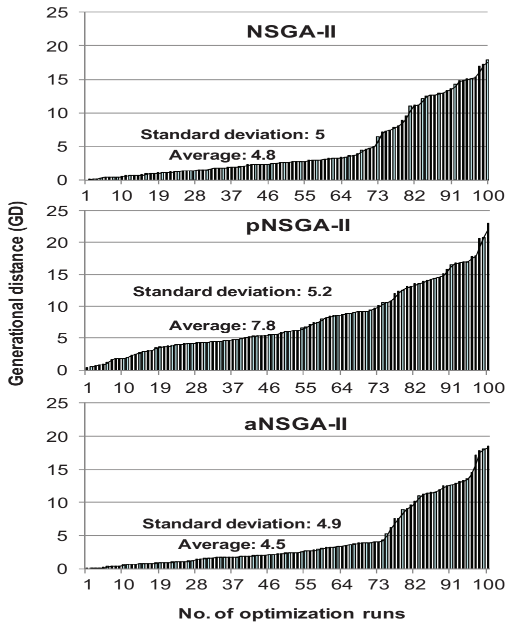

Figure 7 Convergence metric (GD) for 100 optimisation runs

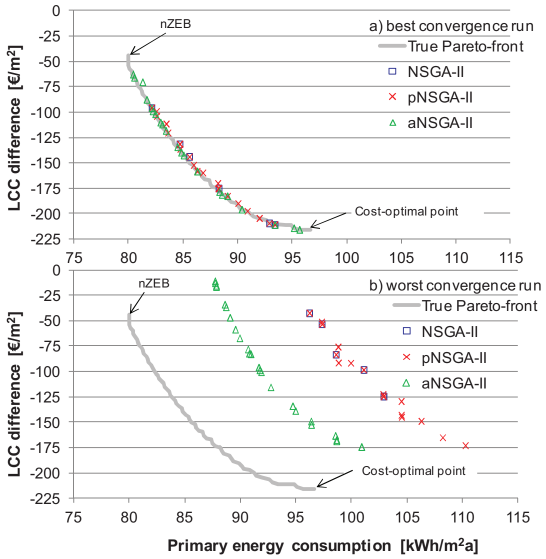

Figure 8 True Pareto-front and found solutions at (a) the best and (b) the worst convergence runs in 100 optimisation runs

The influence of increasing the number of the generations on the convergence is shown in Figure 9. Assuming a fixed population size (six individuals) and crossover probability (0.9) as above, 100 optimisation runs are repeated at different number of generations. It is clear that *GD* for the three algorithms is decreasing with increasing the number of the generations. However, the performance of the aNSGA-II is progressively improving with increasing the number of the generations, while the other two algorithms appear to be unstable in this respect. Because of the limited population size, the original NSGA-II could loss potentially Pareto-optimal solutions during the optimisation runs. Increasing the number of generations could not resolve this problem. Using a large number of generation increases the pNSGA's *NS*. This could lead to deceptive large value of average-*GD*.

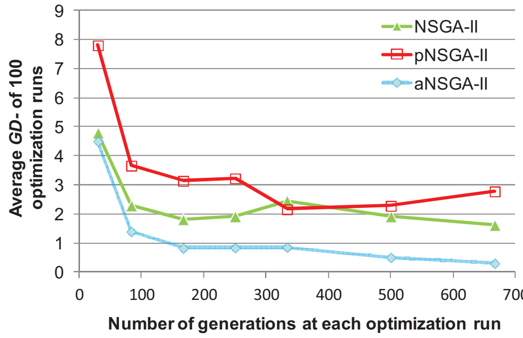

Figure 9 Average GD of 100 optimisation applying different number of generations

COST-OPTIMALITY AND NEARLY-ZERO ENERGY BUILDING RESULTS

The true-Pareto front and the obtained solutions from the optimisation algorithms are indicated in Figure 8. The cost-optimal solution is the solution that has the minimum LCC, while the nearly-zero-energy solution, nZEB, is the solution that has the minimum primary energy consumption PEC. The points between the above mentioned two solutions represent various solutions extending from the cost-optimal solution towards the nZEB solution.

Table 3 shows the range of the design options found on the true-Pareto optimal front and of the cost-optimal point. These are results from the exhaustive search indicated earlier. From these results, we can conclude that some of the design variables (e.g. the type of the building envelope, HU-1 and HU-2) have a strong impact on the objective functions (LCC and PEC), while others have weaker ones.

Table 4 and 5 present the optimal design options found by pNSGA-II and aNSGA-II, in the best and the worst convergence runs, using 180 evaluations. The worst convergence runs show that the algorithms could occasionally fail to get close to the Pareto-optimal front, particularly if a low number of evaluations is used (Figure. 8b). The reason is that the algorithms could select non-optimal design options. The exhaustive search (Table 3) shows that it is economically feasible to invest in GSHP and ‘’120 or 950 W’’ micro-wind turbine (µWT) for heating and electricity production, respectively. In the worst convergence runs, pNSGA-II and aNSGA-II selected less investments (zero µWT size and/or district heating), (Tables 4 and 5).

In the best convergence runs the cost optimal point is exactly not caught, Figure 8a. The exhaustive search shows that it is not cost-optimal to invest in PV system and/or large size of µWT (e.g., 400 or 950 W), Table 3. pNSGA-II and aNSGA-II selected the largest size of µWT (950 W). Furthermore, pNSGA-II considered 3m^2 of PV as a minimum.

Most of the non-optimal selections, shown in Table 4 and 5, are avoided and better convergences are achieved when larger number of evaluations (≥ 500) are implemented. The figure shows that the presented aNSGA-II has a higher repeatability to achieve close-to optimal solutions than the other two algorithms (NSGA-II and pNSGA-II).

Table 3 Optimal solutions on the true Pareto-front

DESIGN VARIABLES	TRUE-PARETO RANGE	COST-OPTIMAL POINT
Building envelope	Passive house	Passive house
Type of HU-1 (primary)	GSHP	GSHP
Type of HU-2 (auxiliary)	Gas boiler	Gas boiler
Size of µWT [W]	120 or 950	120
η of the heat recovery unit	80 %	80 %
Photovoltaic area [m^2]	0-60	0
T_{out} from HU1 [^{o}C]	44 or 52 ^{o}C	44 ^{o}C
Size of the heating coil of the DHW tank (% of the max. size)	100 %	100 %
Size of HU-1 (% of the peak heating load)	50-100%	50 %

Table 4 The optimal solution ranges found by pNSGA-II in the best and the worst runs using 180 evaluations

	SOLUTIONS RANGE	
DESIGN VARIABLES	BEST RUN	WORST RUN
Building envelope	Passive house	Passive house
Type of HU-1 (primary)	GSHP	DH
Type of HU-2 (auxiliary)	Gas boiler	Gas boiler
Size of µWT [W]	950	0
η of the heat recovery unit	80 %	80 %
Size of photovoltaic [m^2]	3-45	0-51
T_{out} from HU1 [^{o}C]	44 ^{o}C	44-60 ^{o}C
Size of the heating coil of the DHW tank (% of the max. size)	100 %	100 %
Size of HU-1 (% of the peak heating load)	50-90%	60-90 %

Table 5 The optimal solution ranges found by aNSGA-II in the best and the worst runs using 180 evaluations

DESIGN VARIABLES	SOLUTIONS RANGE	
	BEST RUN	WORST RUN
Building envelope	Passive house	Passive house
Type of HU-1 (primary)	GSHP	DH
Type of HU-2 (auxiliary)	Gas boiler	Gas boiler
Size of µWT [W]	950	950
η of the heat recovery unit	80 %	80 %
Size of photovoltaic [m^2]	0-57	0-60
T_{out} from HU1 [^{o}C]	44 ^{o}C	40-44 ^{o}C
Size of the heating coil of the DHW tank (% of the max. temperature limit)	100 %	100 %
Size of HU-1 (% of the peak heating load)	50-80%	60-100 %

PERFORMANCE RESULTS WITH BENCHMARK TESTS

This section tests the performance of the original NSGA-II and the presented aNSGA-II using mathematical Bi-objective benchmark test problems (ZDT2 and ZDT3) created by Zitzler, Deb and Thiele (Deb. 2001). The problems have been widely used in comparison studies (David et al., 2000), (Deb et al., 2002) and (Deb and Tiwari, 2005). ZDT2 problem is a non-convex problem, while the difficulty with ZDT3 is the number of disconnected regions in the Pareto-optimal front. Both problems are 30-variable problems. NSGA-II and aNSGA-II are run for thirty times for both of the benchmark test problems. For NSGA-II, a population size of 100 individuals is used as in the original study (Deb et al., 2002). A smaller size (10 individuals) is used for aNSGA-II to test its reliability to solve problems using small population size (the raised challenge in this paper). Typical results after 5000 function evaluations (50 and 500 generations of NSGA-II and aNSGA-II, respectively) are shown in Figures 10 and 11. The typical results are the results that have values for both metrics *GD* and *DIV* closest to the average values. Mean values of the convergence and diversity metrics (GD and DIV) are presented in Tables 5. These benchmark test results confirm that the implemented archiving strategy can combine better convergence with diversity in evolutionary multi-objective optimisation problems. With small population size, aNSGA-II does not lose potential Pareto-optimal solutions and provides a large number of solution lie on or close-to the true Pareto-front.

Table 5 Results of the benchmark tests

PROBLEM	NSGA-II		aNSGA-II	
	GD	*DIV*	*GD*	*DIV*
ZDT2	0.307	0.8363	0.0094	0.766
ZDT3	0.1099	0.8186	0.0124	0.925

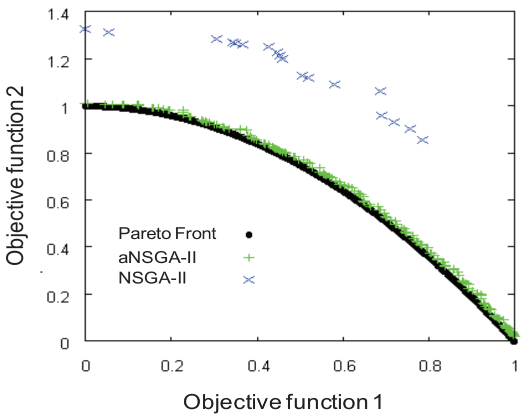

Figure 10 Optimal results for the ZDT2 benchmark test problem

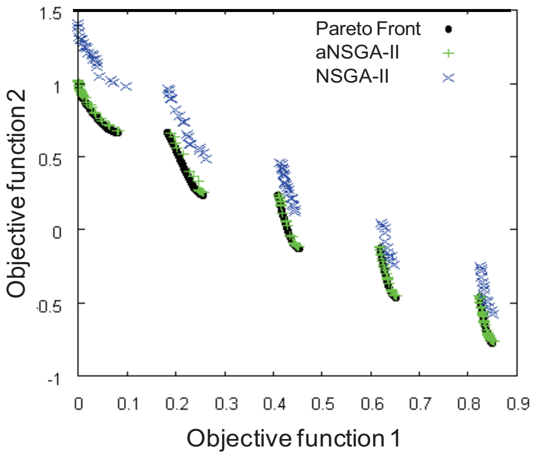

Figure 11 Optimal results for the ZDT3 benchmark test problem

CONCLUSIONS

This is one of the first studies that use simulation-based optimisation in finding the cost-optimal and nearly-zero energy building (nZEB) solutions for a problem that is in accordance with the implementation of the new EPBD-2010. In this study, a holistic optimisation approach is implemented for solving the problem by taking together various design variables in the building envelope, type of heating systems, renewable energy sources and operating temperatures. The simulation is kept relatively simple in order to speed up the comprehensive analysis process. The aim of the research is to test aNSGA-II algorithm, rather than to answer particular questions about building design.

The performance of three multi-objective elitist non-dominating sorting algorithms (original NSGA-II, pNSGA-II, and aNSGA-II) was tested for finding the optimal solutions for a cost-optimal and nZEB design problem. The tests were carried out using 100 optimisation runs with different number of evaluations ranging from 180 to 4000 evaluations per run. The results indicate that aNSGA-II (NSGA-II with active archive) has a better repeatability in finding optimal solutions with high convergence than the original NSGA-II and NSGA-II with a passive archive strategy (pNSGA-II). A main advantage of aNSGA-II is that it found high-quality solutions close to the true-Pareto front using a low number of evaluations. This is advantageous especially for HVAC and building optimisation problems that have time-consuming simulation runs. With a larger number of evaluations, it is found that aNSGA-II achieved better convergence than the two other algorithms. These features of aNSGA-II were also confirmed when testing it with two benchmark test problems (ZDT2 and ZDT3).

For the studied case, it was found that the passive house building-envelope and the GSHP heating system are the optimal solutions. The cost-optimal size of the GSHP is 50% of the peak heating load. Higher percentages lead to higher energy performance towards nZEB. In order to improve the GSHP efficiency, it is economically feasible to operate it for a low supply water temperature (e.g. 44^{o}C). Higher temperatures (up to 52 ^{o}C) are also found optimal, particularly with small GSHP sizes. It is found that it is economically feasible to use photovoltaic panels (PV) and micro wind turbine (µWT) in the solutions towards nZEB. The PV and µWT produce electricity not only for the lighting and the appliances, but also for indirect heating via the GSHP. Using the largest sizes of PV and µWT in integration with GSHP, achieved nZEB with about 80 kWh/m^{2}a primary energy consumption.

Our future work will seek to test other optimisation algorithms on bigger scale problems, including the cost-optimality and nZEB problem.

NOMENCLATURE

aNSGA-II Active-Archive NSGA-II
COP Coefficient of Performance
DH District Heating
DIV Diversity of solutions in the Pareto-optimal set
GD Generational Distance
GSHP Ground Source Heat Pump
HU-1 Heating Unit (primary unit)
HU-2 Heating Unit (auxiliary unit)
LCC Life Cycle Cost
NSGA-II Elitist Non-dominated Sorting Genetic Algorithm
NS Number of Solutions
nZEB Nearly-Zero Energy Buildings
PEC Primary Energy Consumption
pNSGA-II Passive-Archive NSGA-II
*P** True-Pareto front
µWT Micro-wind turbine (roof-mounted)

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